Risk of nonresponse bias and the length of the field period in a mixed-mode general population panel

Bella Struminskaya, Utrecht University
Tobias Gummer, GESIS – Leibniz Institute for the Social Sciences

Mini-paper to be presented at the 28th International Workshop on Household Survey Nonresponse, August 30 – September 1, 2017 in Utrecht. This is work in progress, please do not cite without contacting the authors.

Introduction

Longer fielding period might lead to higher participation but it also requires more time and effort from survey managers and the resulting data cannot be produced as timely as with shorter fielding time. However, shortening the field period to reduce survey costs might introduce the risk of nonresponse bias. Several studies found differences between respondents who respond fast after receiving the survey request (early respondents) and those who take longer time to respond (late respondents). The literature on comparing early and late respondents reports demographic and substantial differences (Bates and Creighton 2000; Dalecki et al. 1992; De Rada 2005; Duhart 2001; Green et al. 1991; Kennikell 2008; Kruse et al. 2010; Rao and Pennington 2013; Sigman et al. 2014; Voigt et al. 2003) as well as differences in data quality (Bates and Creighton 2000; Newman 1962; Rao and Pennington 2013; Voigt et al. 2005). Thus, our research questions are:

1) Does a longer fielding time reduce the risk of nonresponse bias?
2) Do the online and the mail modes differ in terms of optimal length of the field period?

Data

We use the data from the GESIS Panel, a mixed-mode probability-based panel of the general population in Germany aged 18 to 70 (N of the active panel is 4938). About 65% of the respondents complete the surveys online, while about 35% respond via mail questionnaires (for a detailed description of the GESIS Panel see Bosnjak et al. 2017). The field period for each wave is set at two months for both online and mail modes with six panel waves per year. All respondents receive an invitation letter with a prepaid 5 euros incentive, for offline panel members a paper questionnaire and a return envelope are enclosed. In addition to a postal invitation, online panel members receive an email invitation and two email reminders after about one week and two weeks from the invitation date. The recruitment process included a face-to-face interview and a first self-administered (online or offline) survey, the welcome survey.
We use the data from six panel waves, starting with the first wave after the completion of the recruitment process: February-March 2014, August-September 2014, February-March 2015, August-September 2015, February-March 2016, and August-September 2016. We chose the first and the fourth wave of every year to analyze changes over time while excluding the influence of holiday seasons in which response times might follow somewhat different patterns. For the selected waves, the completion rates for the waves vary between 90.7% and 92.8% for online respondents and 82.4% and 90.1% for offline respondents. The cumulative response rates vary between 20.6% and 21.2% for the online mode and 19.3% and 21.1% for the offline mode (Schaurer et al. 2014; Tanner et

al. 2014; Tanner et al. 2015; Schaurer et al. 2015; Struminskaya et al. 2016; Schaurer and Pötzschke 2016).

Methods

As an indicator of the risk of nonresponse bias we use the coefficient of variation (Schouten et al. 2009)

$$CV = \frac{\sigma_\rho}{\bar{\rho}}$$

where σ_ρ is the variation in response propensities and $\bar{\rho}$ is the actual response rate. According to the stochastic approach to survey participation, each respondent has a theoretical probability to participate in a survey (Bethlehem 2002; Groves 2006), the so called response propensity. Respondents with low propensities are placed towards the lower end of the reluctance continuum, while respondents with high propensities are placed near the higher end (Kaminska et al. 2010). We calculate response propensities (ρ) separately for online and offline respondents using logistic regression (dependent variable: response vs. nonresponse) with 28 independent variables collected during the face-to-face recruitment interview and in the first self-administered survey. The variables we chose reflect the mechanisms of survey participation (Groves and Couper 1998), and reflect time availability, civic engagement, previous survey experience that was shown to influence the willingness to participate in next waves of a longitudinal survey (Hill and Willis 2001; Olsen 2005; Watson and Wooden 2009), and longitudinal burden (Apodaca et al. 1998). These variables include age, gender, level of education, marital status, employment status, being a citizen of the country, household size and having young children in the household, being a low-income household, likelihood to move, life satisfaction, trust, political interest, attitudes towards importance of family and importance of free time, satisfaction with the country's government, democracy, and economy, value of political engagement, online or offline mode, and interviewer-generated information on using the incentive information to persuade the respondent to participate in an initial recruitment interview, assessment how easy it was to persuade the respondent to participate in the panel, and respondents' assessed social class, overall evaluation of the first self-administered survey and whether this survey was considered burdensome.

Based on our comprehensive propensity model, we calculate the coefficients of variation (CV) for every day during field period and then compare the CV trends between the modes. For each of these calculations, we include the respondents who have participated in the respective panel wave until a given day during the field period.

The date of each respondent's participation in a panel wave is provided through an automatically generated time stamp for online respondents and the self-reported date of completing the mail questionnaire for offline respondents.

Results

Below we show the plots of the coefficient of variation for the six waves we analyze. Overall, the pattern is the same for all waves with the CV decreasing in the course of the fiel period. We do find that there are differences in the risk of nonresponse bias by mode with the risk of nonresponse bias stabilizing after about 1 week for online respondents while the risk of nonresponse bias stabilizes after about 2 weeks for offline respondents. Hence, the reduced length of the field period would increase the risk of nonresponse bias. The differences between the online and offline modes become less pronounced over the waves. In addition to visually examining the plots, we calculate the optimal length of the fielding period for each wave in each mode by looking whether the coefficient of variation on a given day is significantly different from the "optimal" CV when all respondents would participate regardless of their response propensity. Preliminary results show that the optimal cut-off for the online mode would be around ten days after the fieldwork start, while optimal cut-off dates for the offline mode show more variation and lie between 14 to 20 days. Note that these findings are still preliminary and are subject to change.

Conclusion

In the present study, we have proposed a method that allows to estimate the optimal field period length considering the risk for nonresponse bias. This can be done for different surveys and across different modes if data from previous comparable surveys are avaible. This offers considerable potential for cost savings especially in face-to-face longitudinal surveys.

Figure 1. Coefficient of variation for Wave 1:

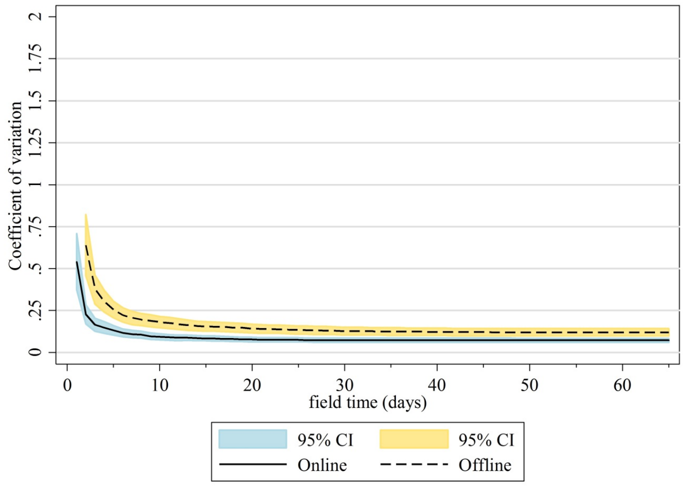

Figure 2. Coefficient of variation for Wave 2:

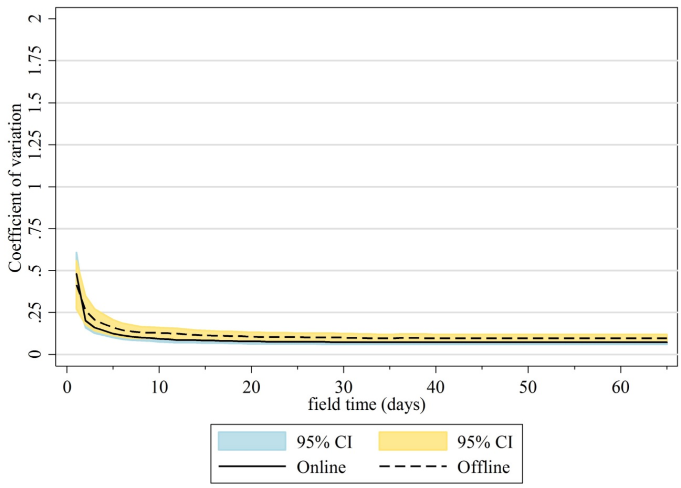

Figure 3. Coefficient of variation for Wave 3:

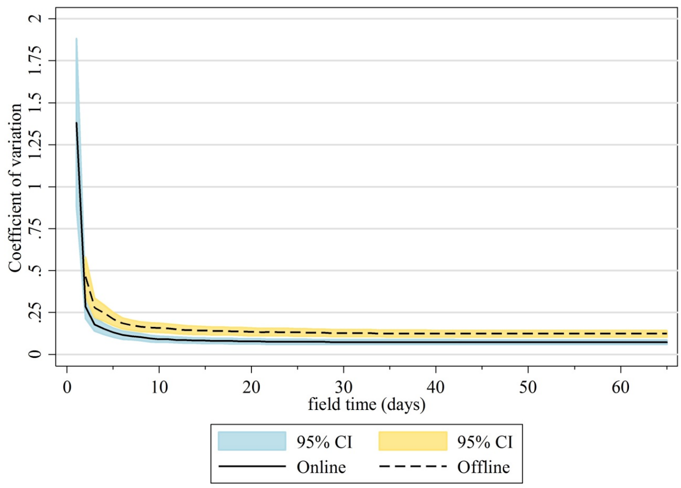

Figure 4. Coefficient of variation for Wave 4:

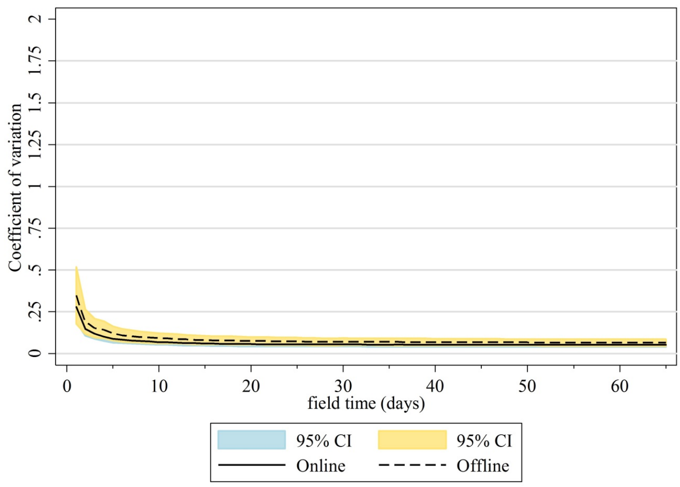

Figure 5. Coefficient of variation for Wave 5:

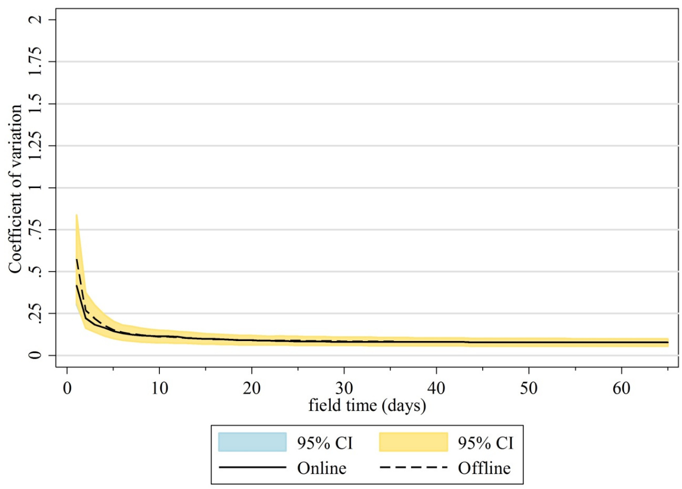

Figure 6. Coefficient of variation for Wave 6:

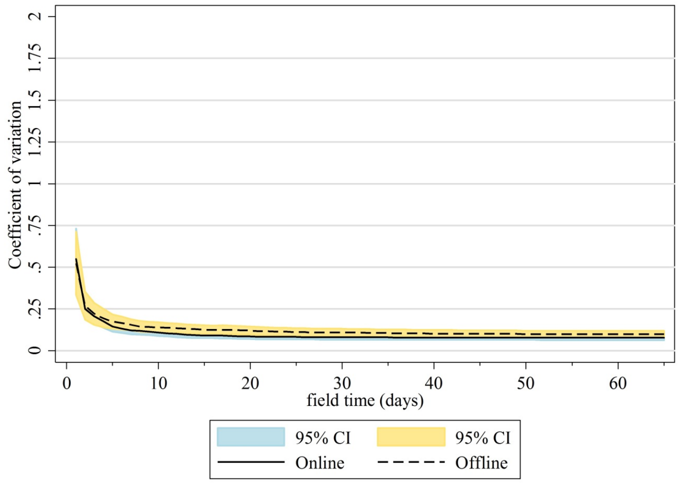

Figure 7. Optimal cut-off date by mode.

Points for discussion with participants:

1) Using the coefficient of variation vs. R-indicators;
2) Using other metrics for defining the optimal field period length, e.g., 0.02 of the previous / final CV value as well as using thresholds of 0.01 and 0.05 (Moore, Durrant & Smith 2016);
3) Addressing generalizability beyond self-administered surveys.